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SUSTAINABLE SUPPLY CHAIN NETWORK DESIGN

Closed-loop supply chain network design with sustainability and resiliency criteria

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Abstract

Today, the research on the closed-loop supply chain network design with sustainability and resiliency criteria is a very active research topic. This paper provides a new closed-loop supply chain under uncertainty with the use of resiliency, sustainability, and reliability dimensions among the first studies. To model this problem, a two-stage stochastic programming approach is used. To create robust solutions against uncertainty, a conditional value at risk criterion is contributed. The proposed model aims to minimize the total cost, environmental pollution, and energy consumption while maximizing the job opportunities as the social factor. In addition to the sustainability goals, the energy consumption is considered to be the last objective to be minimized. To show the applicability of the proposed model, an automobile assembler industry is applied. To solve the model, the Lp-metric method is employed to transform this multi-objective model into a single objective one. Since this closed-loop supply chain model is complex and NP-hard, a Lagrangian relaxation method with fix-and-optimize heuristic is employed to find the upper and lower bounds for the model via different random test problems. With an extensive analysis, the proposed model shows an improvement to the total cost, CO_2 emissions, job opportunities and energy consumption.

Keywords Closed-loop supply chain · Reliability · Resilience · Risk management · Robust optimization · Sustainability

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Introduction and literature review

One of the purposes of designing a closed-loop supply chain (CLSC) is to form a network, launching and operating the material flow between the chain centres so that the economic, environmental, and social goals of the beneficiaries are simultaneously optimized. Further, creating and promoting sustainable development to design a CLSC (Zhang et al. 2020; Liu et al. 2020; Meixell and Gargeya 2005). In addition to the trend of sustainability which is contributed to the economic, environmental, and social goals simultaneously, demand uncertainty is always an active concept in the CLSC management (Talaei et al. 2016). In the case of disaster like flood or earthquake or terrorist attacks, the supply chain resiliency is very important to manage the demand uncertainty (Yu et al. 2021; Fathollahi-Fard et al. 2020a). These changes have created a growing demand uncertainty which highlights the significance of a robust and well-designed supply chain network (SCN) (Melo et al. 2009).

It goes without saying that the SCN must be reliable when the CLSC is under uncertainty. Considering facility reliability against disruption conditions such as flood, storm, and

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earthquake is among the recent developments which have been added to the supply chain by researchers (Khalilpourazari and Mohammadi 2016; Torabi et al. 2016). In addition to the reliability, sustainability, and resiliency dimensions, the energy consumption is rarely contributed in the literature. An energy-efficient SCN is useful to be reliable and sustainable (Fang and Xiao 2013; Mari et al. 2016; Ghomi-Avili et al. 2017; Golshahi-Roudbaneh et al. 2017). Therefore, the present study contributes to the literature by designing a robust optimization model for sustainable and resilient CLSC network design by considering conditional value at risk (CVaR).

The literature of CLSC management is very old, and there are many studies with an introduction to the resiliency, reliability, and sustainability (Kleindorfer and Saad 2005; Klibi et al. 2010; Pishvaee et al. 2014; Hajiaghaei-Keshteli and Fard 2019; Abdi et al. 2020). For example, a reliable CLSC is suggested by Torabi et al. (2016), which can be used where the facilities have disruption. The innovation in this model is related to using stochastic *p*-robust optimization approach in facing disruption in the facility (Fathollahi-Fard et al. 2020d, 2020e). In addition, the proposed model includes both partial and complete disruption in the facility capacity and is modelled as fuzzy. The results of the study indicated that considering disruption increases the costs and optimizes the system against disturbance. Talaei et al. (2016) defined a bi-objective SCN model with the consideration of reverse logistics and CO_2 emissions. A reliable and resilient CLSC under-supply risk is designed by Ghomi-Avili et al. (2017). They focused on the strategic inventory levels to improve the resiliency. In addition, they considered the financial risk to make reliable decisions in a CLSC network.

The quality levels for the products and considering the product complexity is another active topic in the CLSC management. For example, Tavakkoli-Moghaddam et al. (2015) proposed a location-routing problem with time windows and earliness and tardiness costs. They considered a multi-echelon SCN with supplier selection, facility location and allocation, routing of transportation systems, and different quality levels of the products. A fuzzy possibilistic approach was employed to address the uncertainty. Mari et al. (2014) designed a sustainable and resilient SCN in the textile industry. They contributed to the sustainability with the consideration of CO_2 emissions and the resiliency with the possibility of disruptions in the facilities. In another study, Amin and Baki (2017) developed an optimization model for the CLSC management containing global factors such as exchange rate and customs duties. They applied a case study of electronic products to focus on the recycling and reusing of e-wastes. Furthermore, Amin et al. (2017) among the first study applied a CLSC for the tire industry. They also considered the demand uncertainty with the use of fuzzy logic. With a contribution to the supply chain resiliency, Nezhadroshan et al. (2020) developed a resilient humanitarian supply chain network design problem. Their multi-objective optimization model a scenario-based robust-possibilistic programming method optimizes the total cost, the total time, and resilience level of facilities, simultaneously.

Recently, the sustainable CLSC management is very active, and many researchers have applied this issue in different industries. For example, Sahebjamnia et al. (2018) designed a resilient CLSC in the tire industry. Their model is developed for economic, environmental, and social goals. They employed four hybrid methods including red deer algorithm (RDA) and simulated annealing (SA) algorithm, genetic algorithm (GA) and water wave optimization (WWO) algorithm, WWO and tabu search (TS) algorithms, and RDA and WWO algorithm for solving the model. They indicated that GA and WWO algorithm are more efficient. Recently, Fathollahi-Fard et al. (2020a) based on the ReCiPe database optimize a sustainable water supply and wastewater collection system for a case study of Urmia Lake in Iran. They used a social engineering optimizer (SEO) to solve their case study. In another study, they employed an adaptive Lagrangian relaxation-based algorithm to address a resilient water supply chain system (Fathollahi-Fard et al. 2020b).

To assess the literature gaps and the contributions of this research to fill them, Table 1 provided a survey on the CLSC management. The papers are classified by eight criteria. Table 1 evaluates the kind of CLSC, the resilience measures, disruption, uncertainty, risk, objective(s) and the industry application, and finally the solution method. As can be identified from Table 1, the following findings are observed:

- No study has considered a sustainable, resilient, and reliable CLSC with CVaR risk condition.
- Sustainability objectives including economic, environmental, and social goals in addition to the energy consumption are simultaneously considered only by this paper.
- Car manufacturing industry as an application of CLSC option is rarely contributed in the literature.

Generally, this study fills the aforementioned literature gaps. In Section 2, the proposed problem is explained and formulated. In addition, the basic models and the solution approach are introduced. Section 3 does the computational analyses with simulation tests and sensitivity analyses for our case study. Section 4 finally concludes the main findings and future research directions.

Model formulation

Various studies have been performed to design the CLSC network. The main literature gap revealed that there is still

Table 1 Survey on CLSC

Reference	Kind of CLSC	Resilience	Disruption	Uncertainty	Risk	Objectives	Industry	Method
(Torabi et al. 2016)	Reliable	Multiple sourcing and assignment	Both partial, complete disruption	Probabilistic mixed programming	*P*-robust	Economic	Numerical example	Epsilon-constraint
(Ghomi-Avili et al. 2017)	Reliable and resilient	Extra inventory Lateral transhipment Reliable and unreliable suppliers	Complete disruption	Two-stage probabilistic mixed programming	Supply risk	Economic	Numerical example	*CS
(Tavakkoli-Moghaddam et al. 2015)	–	–	–	Possibilistic fuzzy approach	–	Economic	Numerical example	CS
(Mari et al. 2014)	Sustainable and resilient	–	Probabilistic disruption	Probabilistic	–	Economic and emissions of carbon footprints Disruption costs	Textile industry	CS
(Amin and Baki 2017)	–	–	–	Fuzzy programming	–	Economic	Electronics industry	CS
(Amin et al. 2017)	–	–	Scenario	Scenario three	–	Economic	Tire marketing	CS
(Soleimani and Govindan 2014)	–	–	–	Two-stage scenario	CVaR	Economic	Numerical example	CS
(Cardoso et al. 2016)	–	–	–	Stochastic	Variance, *VI, *DR, and CVaR	Economic (ENPV)	Numerical example	*AEC
(Subulan et al. 2015)	–	–	–	Stochastic fuzzy and possibilistic	VaR, CVaR, and downside risk	Economic and the average of the collected volume of the used products	Lead-acid battery	CS
(Prakash et al. 2017)	Robust and reliable	–	Scenario	Stochastic	Worst risk case	Economic	Electronics trade industry	CS
(Prakash et al. 2018)	Reliable	–	–	Convex robust	Waiting times	Economic	Hospital beds	CS
(Sahebjamnia et al. 2018)	Sustainable and resilient	–	–	–	–	Economic, environmental, and social	Tire industry	*MH
(Fathollahi-Fard et al. 2020a)	Resilient	–	Scenario	Stochastic	–	Economic	Water and wastewater system	Lagrangian relaxation
(Behzadi et al. 2018)	Resilient	Diversified demand market, backup demand market, and flexible rerouting	Scenario	Robust optimization two-stage stochastic	–	Economic	Kiwifruit	CS
(Brandenburg 2015)	Sustainable	–	Scenario	Stochastic	–	Economic and environmental	FMCG manufacturer	*WGP
(Brandenburg 2017)	Green	–	–	Simulation	VaR	Economic and environmental		CS

Table 1 (continued)

Reference	Kind of CLSC	Resilience	Disruption	Uncertainty	Risk	Objectives	Industry	Method
							Numerical example	
Fathollahi-Fard et al. (2020b)	Sustainable	–	Scenario	Stochastic	–	Economic, environmental, and social	Water and wastewater	SEO
(Yavari and Zaker 2020)	Sustainable and resilient	Reserving extra capacity, keeping emergency stock, lateral transhipment, intermediate facility	Disruption	Stochastic	–	Economic and environmental	Dairy company	CS
Nezhadroshan et al. (2020)	Resilient	Reserving extra capacity, keeping emergency stock, and resilience levels of facilities	Scenario	Robust-possibilistic	–	Economic, travel time, and resiliency	Numerical example	AEC
The present study	Sustainable, resilient, and reliable	Capacity	Partial disruption	Stochastic	CVaR	Economic, environmental, energy, and social	Car manufacturing industry	CS NEOS

***NA* not applicable, *DR* downside risk, *VI* variability index, *WGP* weighted goal programming, *CS* commercial solver, *MH* RDA and SA algorithm, GA and WWO algorithm, *AEC* augmented epsilon constraint

an opportunity to integrate a sustainable, reliable, and resilient CLSC network with the use of robust optimization to control demand variations, resilient, and risk-averse rates. The present study aims to investigate the car manufacturing industry. Considering the initiation of manufacturing old and new cars in Iran, this paper designs a CLSC to meet the sustainability dimensions including financial, environmental, energy, and social requirements. A graphical justification of the proposed problem is given in Fig. 1. Then, the research methodology in this paper is provided in Fig. 2.

The model aims at minimizing the costs, environmental pollutant emissions, and energy consumption as well as maximizing the employment rate, which is one of the social welfare indexes. We consider the disruption risk of each scenario and whether it is robust against demand variation. Further, this model applies cumulative energy demand (CED), guidelines for social life cycle assessment of products (GSLCAP), and ReCiPe solutions to assess the effects on the sustainability dimensions. The demands of the final customers in the proposed model have various scenarios to show the strategic decisions in the proposed model.

Robust optimization concept proposed by Mulvey et al. (1995) is applied in the present study to achieve common business uncertainty and existing disruptions. Moreover, our approach includes minimizing the sum of the weighted average and standard deviation of an objective function, i.e. costs, environmental goal, energy, employment, and a fine related to not satisfying a key limitation, i.e. demand. Offering flexibility and adding to the supply and production capacities are considered the resilience strategy used to face with losing capacities of suppliers and factories resulting from disturbances (Torabi et al. 2016). Further, we involved a flexible capacity facility depending on the scenario, and we used an availability parameter to represent a reliable facility with disruption (Zhang et al. 2014).

A scenario-based stochastic programming developed by Mulvey et al. (1995) is as follows (Eqs. (1), (2), (3), and (4)):

$$Min\ c^T x + d^T \tag{1}$$

Such that:

$$Ax = b, \tag{2}$$

$$Bx + Cy = e, \tag{3}$$

$$x, y \geq 0 \tag{4}$$

Assuming that the variable y is dependent on the scenario, and for each scenario $s \in \Omega$, the modelling is as follows. The objective function is the mathematical expectation and absolute deviation from the objective function of the target function for each scenario (Eqs. (5), (6), (7), (8), (9), (10), and (11)):

$$Min\sigma(x,y_s)+\omega p(z_s) \quad (5)$$

Such that:

$$\sigma(x,y_s)=\sum_{s\in\Omega}p_s\Gamma_s+\beta\sum_{s=1}^{N}p_s\left|\Gamma_s-\sum_{s=1}^{N}p_s\Gamma_s\right|,\quad \forall s\in\Omega \quad (6)$$

$$p(Z_s)=\sum_{s\in\Omega}p_s|Z_s|,\forall s\in\Omega \quad (7)$$

$$\Gamma_s=c^Tx+d^Ty_s,\quad \forall s\in\Omega \quad (8)$$

$$Ax=b,\quad \forall s\in\Omega \quad (9)$$

$$Bx+Cy_s+z_s=e,\quad \forall s\in\Omega \quad (10)$$

$$x,y_s\geq 0,\quad \forall s\in\Omega \quad (11)$$

Since CVaR has a unique feature and brilliant performance, the present study adds a risk measure to the model in the network design of the closed-loop supply chain as follows (Sorokin et al. 2013) (Eqs. (12), (13), and (14)).

$$\min_{x\in R^n}\left\{E\Big(f(x,w)+\lambda CVaR(f(x,w))\Big)\right\} \quad (12)$$

$$CVaR_\alpha(Z)=\min_{\eta\in\mathbb{R}}f(\alpha,\eta,x) \quad (13)$$

$$f(\alpha,\eta,x)=\eta+\frac{1}{1-\alpha}E\{max\{Z(x,\omega)-\eta,0\}\} \quad (14)$$

Since the solution scenario in the model is based on the scenario analysis approach, considering previous studies, the following rewrite for designing and planning the supply chain can be used (Noyan 2012) (Eq. 15).

$$Min\sigma(x,y_s)+\omega p(z_s)+\lambda CVaR(x,y_s) \quad (15)$$

Such that:

Constraints (A−6) to (A−11)

In mathematical optimization, nonlinear functions or components within can be linearized to apply a linear solving method such as the linearization method (Fathollahi-Fard et al. 2020c). Since the proposed model includes the absolute value function and max type functions and it is nonlinear, the common operational research methods are used to linearize the objective function by removing the absolute value function until obtaining an optimal and global solution (Hill and Ravindran 1975).

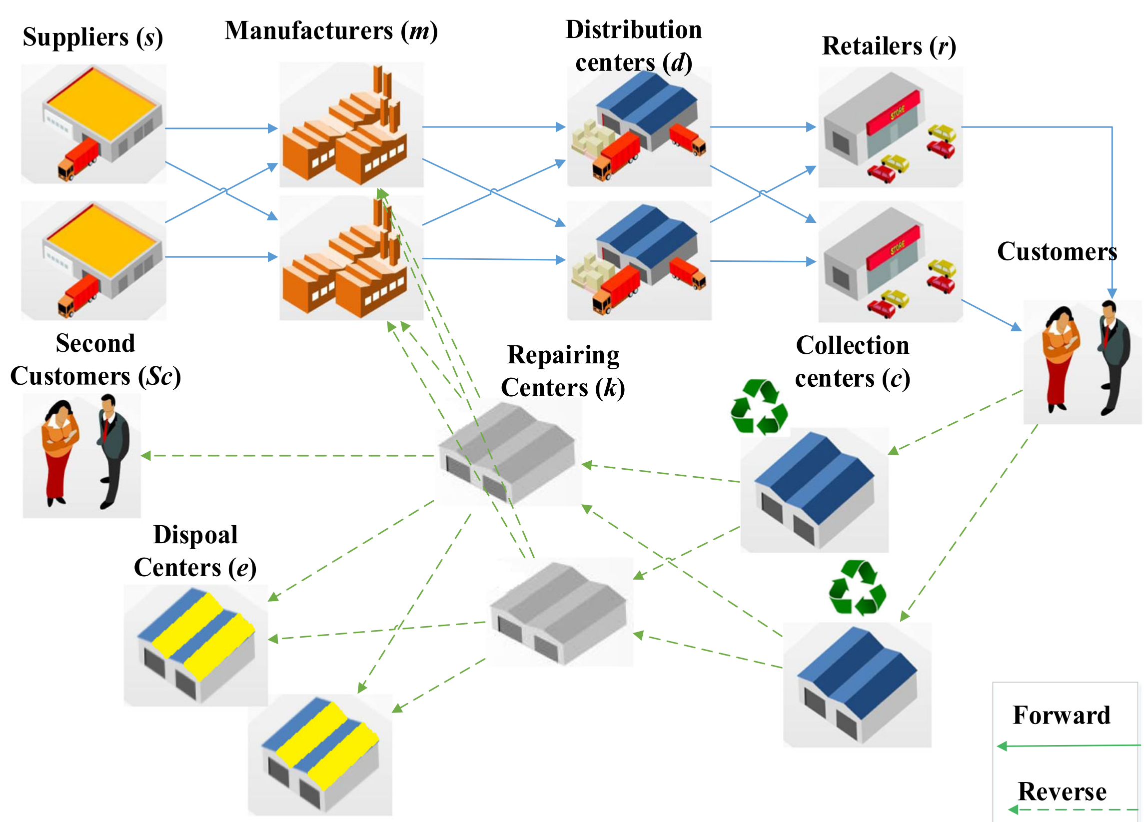


Fig. 1 Proposed CLSC network

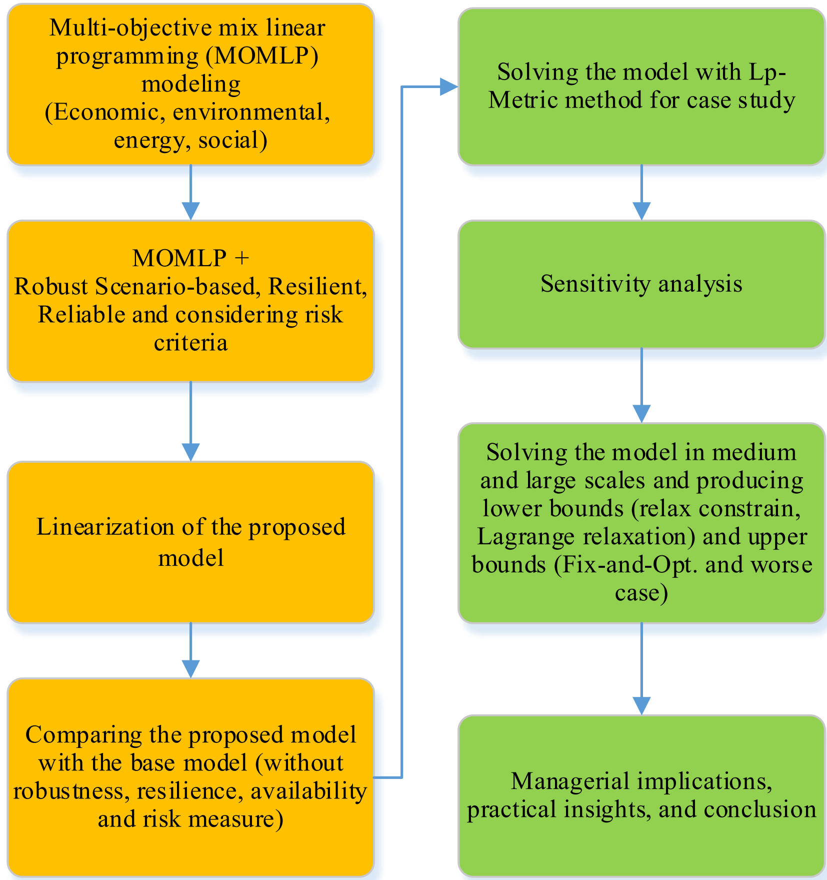


Fig. 2 Research methodology

$$minobj_1 = \sum_{s'} p_{s'} \Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left(va_{s'} + vb_{s'}\right) + \omega \sum_{s} p_{s'} k_{s'1} \left(\sum_r \sum_p \sum_t \left(vc_{rpts'} + vd_{rpts'}\right)\right) + \lambda \left(\eta_1 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} ve_{s'}\right), \tag{16}$$

$$minobj_2 = \sum_{s'} p_{s'} \Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left(vf_{s'} + vg_{s'}\right) + \omega \sum_{s} p_{s'} k_{s'2} \left(\sum_r \sum_p \sum_t \left(vc_{rpts'} + vd_{rpts'}\right)\right) + \lambda \left(\eta_2 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} vh_{s'}\right), \tag{17}$$

Such that:

$$\Gamma_{s'1} - \sum_{s'} p_{s'} \Gamma_{s'1} = va_{s'} - vb_{s'}, \quad \forall s' \tag{18}$$

$$z_{rpts'} = vc_{rpts'} - vd_{rpts'}, \quad \forall r, p, t, s' \tag{19}$$

$$ve_{s'} \geq \Gamma_{s'1} - \eta_1, \quad \forall s' \tag{20}$$

$$\Gamma_{s'2} - \sum_{s'} p_{s'} \Gamma_{s'2} = vf_{s'} - vg_{s'}, \quad \forall s' \tag{21}$$

$$vh_{s'} \geq 0, \quad \forall s' \tag{22}$$

$$\Gamma_{s'3} - \sum_{s'} p_{s'} \Gamma_{s'3} = vi_{s'} - vj_{s'}, \quad \forall s' \tag{23}$$

$$vk_{s'} \geq \Gamma_{s'3} - \eta_3, \quad \forall s' \tag{24}$$

$$vk_{s'} \geq 0, \quad \forall s' \tag{25}$$

$$\Gamma_{s'4} - \sum_{s'} p_{s'} \Gamma_{s'4} = vl_{s'} - vm_{s'}, \quad \forall s' \tag{26}$$

$$vo_{s'} \geq \Gamma_{s'4} - \eta_4, \quad \forall s' \tag{27}$$

$$vo_{s'} \geq 0, \quad \forall s' \tag{28}$$

$$\boldsymbol{va_{s'}, vb_{s'}, vc_{rpts'}, vd_{rpts'}, vf_{s'}, vg_{s'}, vl_{s'}, vm_{s'} \geq 0}, \quad \forall r, p, t, s' \tag{29}$$

$$\text{min}obj_3 = \sum_{s'} p_{s'} \Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left(vi_{s'} + vj_{s'}\right) + \omega \sum_{s} p_{s'} k_{s'3} \left(\sum_r \sum_p \sum_t \left(vc_{rpts'} + vd_{rpts'}\right)\right) + \lambda \left(\eta_3 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} vk_{s'}\right), \tag{30}$$

$$\text{max}obj_4 = \sum_{s'} p_{s'} \Gamma_{s'4} - \beta \sum_{s'} p_{s'} \left(vl_{s'} + vm_{s'}\right) - \omega \sum_{s} p_{s'} k_{s'4} \left(\sum_r \sum_p \sum_t \left(vc_{rpts'} + vd_{rpts'}\right)\right) - \lambda \left(\eta_4 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} vo_{s'}\right), \tag{31}$$

We can compare the proposed model with Model 2 as follows:

Model 2. Base model (without robustness, resilience, availability, and risk measure)

$$minobj_2 = \sum_{s'} p_{s'} \Gamma_{s'1}, \tag{32}$$

$$minobj_2 = \sum_{s'} p_{s'} \Gamma_{s'2}, \tag{33}$$

$$\text{min}obj_3 = \sum_{s'} p_{s'} \Gamma_{s'3}, \tag{34}$$

$$maxobj_4 = \sum_{s'} p_{s'} \Gamma_{s'4}, \tag{35}$$

Such that:

$$\sum_d Qdr_{drpts'} \geq dem_{rpts'}, \quad \forall r, p, t, s' \tag{36}$$

$$\begin{gathered} prm_m = prd_d = prr_r = prc_c = prk_k = pre_e = 1, \quad \forall m, d, r, c, k, e \\ CapS_{spts'} = CapS_{spt} \quad \forall s, p, t, s' \\ CapM_{mpts'} = CapM_{mpt} \quad \forall m, p, t, s' \\ CapD_{dpts'} = CapD_{dpt} \quad \forall d, p, t, s' \\ CapR_{rpts'} = CapR_{rpt} \quad \forall r, p, t, s' \\ \boldsymbol{CapC_{cpts'} = CapC_{cpt}} \quad \forall c, p, t, s' \\ CapK_{kpts'} = CapK_{kpt} \quad \forall k, p, t, s' \\ CapE_{epts'} = CapE_{ept} \quad \forall e, p, t, s' \end{gathered} \tag{37}$$

As can be seen, objective functions (32), (33), and (34) include minimizing the expected value for cost, environment, and energy. Equation (35) is to consider the employment to create more job opportunities. Equation (36) is the demand satisfaction. Equation (37) ignores the resiliency and reliability for the capacity of facilities. All the above terms attempt to optimize the objective functions in the average scenario case.

In addition, our model can be compared with the mean absolute deviation (MAD) as follows:

Model 3. Risk model with MAD

$$\begin{aligned} \text{min}obj_1 = {} & \sum_{s'} p_{s'} \Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'1} - \sum_{s'} p_{s'} \Gamma_{s'1} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'1} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) \\ & + \lambda \left(\sum_{s'} p_{s'} \left| \Gamma_{s'1} - \sum_{s'} p_{s'} \Gamma_{s'1} \right| \right), \end{aligned} \tag{38}$$

$$\begin{aligned} \text{min}obj_2 = {} & \sum_{s'} p_{s'} \Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'2} - \sum_{s'} p_{s'} \Gamma_{s'2} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'2} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) \\ & + \lambda \left(\sum_{s'} p_{s'} \left| \Gamma_{s'2} - \sum_{s'} p_{s'} \Gamma_{s'2} \right| \right), \end{aligned} \tag{39}$$

$$\begin{aligned} \text{min}obj_3 = {} & \sum_{s'} p_{s'} \Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'3} - \sum_{s'} p_{s'} \Gamma_{s'3} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'3} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) \\ & + \lambda \left(\sum_{s'} p_{s'} \left| \Gamma_{s'3} - \sum_{s'} p_{s'} \Gamma_{s'3} \right| \right), \end{aligned} \tag{40}$$

$$\begin{aligned} \text{max}obj_4 = {} & \sum_{s'} p_{s'} \Gamma_{s'4} - \beta \sum_{s'} p_{s'} \left| \Gamma_{s'4} - \sum_{s'} p_{s'} \Gamma_{s'4} \right| \\ & - \omega \sum_{s'} p_{s'} k_{s'4} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) \\ & - \lambda \left(\sum_{s'} p_{s'} \left| \Gamma_{s'4} - \sum_{s'} p_{s'} \Gamma_{s'4} \right| \right), \end{aligned} \tag{41}$$

As can be seen, objective functions (38), (39), and (40) include minimizing the expected value for cost, environment, and energy and added MAD measure to them. The objective function (41) includes maximizing the expected value for the employment and adds the MAD measure to them.

Model 4. Risk model with VaR:

$$\begin{aligned} \text{min}obj_1 = {} & \sum_{s'} p_{s'} \Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'1} - \sum_{s'} p_{s'} \Gamma_{s'1} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'1} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) + \lambda(\eta_1), \end{aligned} \tag{42}$$

$$\begin{aligned} \text{min}obj_2 = {} & \sum_{s'} p_{s'} \Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'2} - \sum_{s'} p_{s'} \Gamma_{s'2} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'2} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) + \lambda(\eta_2), \end{aligned} \tag{43}$$

$$\begin{aligned} \text{min}obj_3 = {} & \sum_{s'} p_{s'} \Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'3} - \sum_{s'} p_{s'} \Gamma_{s'3} \right| \\ & + \omega \sum_{s'} p_{s'} k_{s'3} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) + \lambda(\eta_3), \end{aligned} \tag{44}$$

$$\begin{aligned} \text{max}obj_4 = {} & \sum_{s'} p_{s'} \Gamma_{s'4} - \beta \sum_{s'} p_{s'} \left| \Gamma_{s'4} - \sum_{s'} p_{s'} \Gamma_{s'4} \right| \\ & - \omega \sum_{s'} p_{s'} k_{s'4} \left(\sum_r \sum_p \sum_t \left| z_{rpts'} \right| \right) - \lambda(\eta_4), \end{aligned} \tag{45}$$

Such that:

$$\inf \eta_u \geq 0, \; F(\Gamma_{s'u}) \geq \alpha, \quad u \in U\{1, \ldots 4\} \tag{46}$$

Constraint (5)−(33).

As can be seen, objective functions (42), (43), and (44) include minimizing the expected value for cost, environment, and energy and added VaR measure to them. The objective function (45) includes maximizing the expected value for the employment and add VaR measure to them. Constraint (46) shows VaR constraint.

In this research, we have four objective functions, and because of more than two objectives and for reducing solution time instead of using posterior methods, it is better to use Lp-metric as follows:

$$minL = \sum_{i=1}^{n} \left[W_i \left(\frac{z_i - \text{min} z_i}{\text{max} z_i - \text{min} z_i} \right)^p \right]^{1/p}, \tag{47}$$

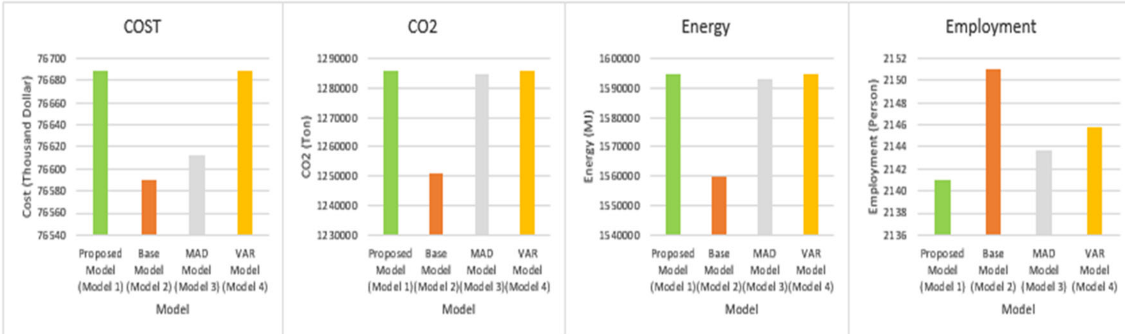


Fig. 3 Comparing the proposed model with the base model, MAD model, and VaR model

Table 2 Comparing the proposed model with the risk model

Objective		Min Z_1	Min Z_2	Min Z_3	Max Z_4	Min Lp-metric
The optimal value of proposed objective function	Cost (Tdollar)	71470.14	174731.64	78459.12	176760.32	76688.59
	Pollutant (CO_2)(C-Ton)	1989597.2	1250941	1317174.2	1734074.6	1285769.7
	Energy (Mj)	2274555.6	1953758.2	1591575.2	2358201.8	1594682.2
	Employ. (Per)	1749	4399	2100	4505	2141
The optimal value of base model (model 2)	Cost (Tdollar)	71357.8	171286.39	76899.32	173265.9	76589.9
	Pollutant (CO_2)(C-Ton)	1901777.2	1217249.6	1258753.3	1650207.1	1251038.2
	Energy (Mj)	2181635.3	1882470.3	1556561	2263490.8	1559701.1
	Employ. (Per)	1788	4499	2150	4520	2151
Avg. gap		1.7%	1.6%	1.6%	2.7%	*1.2%*
The optimal value of MAD model (model 3)	Cost (Tdollar)	71398.586	171306.116	76921.354	173295.300	76611.968
	Pollutant (CO_2)(C-Ton)	1952035.871	1249601.765	1292331.566	1701579.045	1284397.488
	Energy (Mj)	2231425.590	1916445.179	1589903.064	2313426.428	1593005.739
	Employ. (Per)	1784.791	4489.099	2143.154	4510.370	2143.704
Avg. gap		0.5%	0.5%	0.5%	1.4%	**0.05%**
The optimal value of VaR model (model 4)	Cost (Tdollar)	71470.057	171477.457	76998.314	173468.648	76688.619
	Pollutant (CO_2)(C-Ton)	1954075.592	1250908.704	1293683.407	1703371.669	1285741.007
	Energy (Mj)	2233745.832	1918421.837	1591552.059	2315828.354	1594657.770
	Employ. (Per)	1786.569	4493.571	2145.284	4514.862	2145.834
Avg. gap		0.4%	0.4%	0.4%	1.3%	***0.1%***

*Avg. GAP=average (proposed obj_k- obj_k model)/obj_k

Table 3 Weight variations versus objectives

W_1	W_2	W_3	W_4	Cost (Tdollar)	Pollutant (CO_2) (CTon)	Energy (Mj)	Employ. (Person)
0	0.33	0.33	0.33	78143.63	1285793	1594659	2141.56
0.5	0.16	0.16	0.16	76688.59	1285770	1594682	2141.56
1	0	0	0	71470.15	1989597	2274556	1749.06
0.33	*0*	0.33	0.33	76689.36	1316802	1591633	2141.56
0.16	*0.5*	0.16	0.16	79603.18	1274957	1612078	2214.48
0	*1*	0	0	174731.6	1250941	1953758	4399.22
0.33	0.33	*0*	0.33	81873.39	1270004	1672336	2340.66
0.16	0.16	*0.5*	0.16	76688.97	1289052	1592359	2141.56
0	0	*1*	0	78459.12	1317174	1591575	2100.21
0.33	0.33	0.33	*0*	76688.59	1285770	1594682	2100.75
0.16	0.16	0.16	*0.5*	76688.59	1285770	1594682	2141.56
0	0	0	*1*	176760.3	1734075	2358202	4505.85
0.25	*0.25*	*0.25*	*0.25*	76688.59	1285769.68	1594682.21	2141.55

Such that:

$$z_i = f_i(X_1, X_2, \ldots, X_n), \quad i = 1, 2, \ldots, n, \tag{48}$$

$$g_j(X_1, X_2, \ldots, X_n) \leq b_j. \quad j = 1, 2, \ldots, m. \tag{49}$$

Results

Considering various car manufacturing companies in Iran, a suitable CLSC should be designed, which includes the collection, repairing, and disassembling centres, and the steps of the reverse chain should be appropriately redesigned. The case

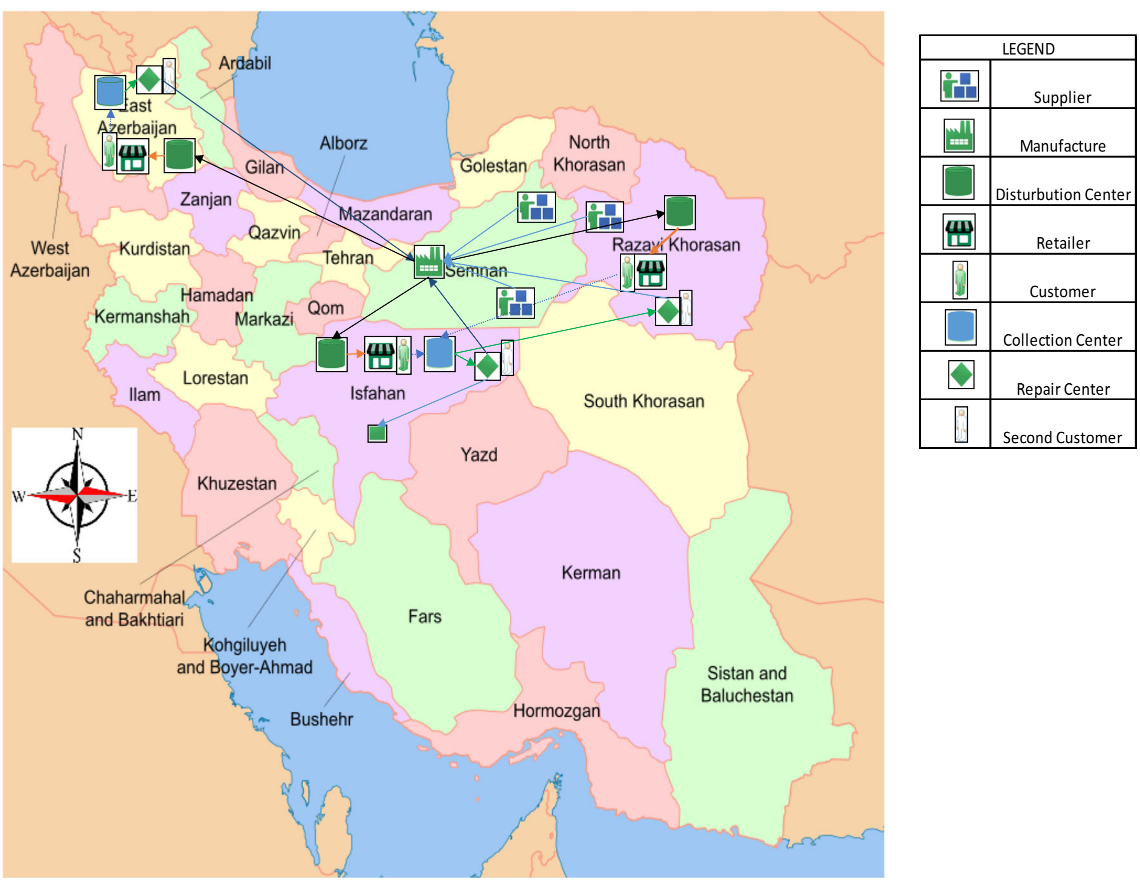


Fig. 4 Map of the case study

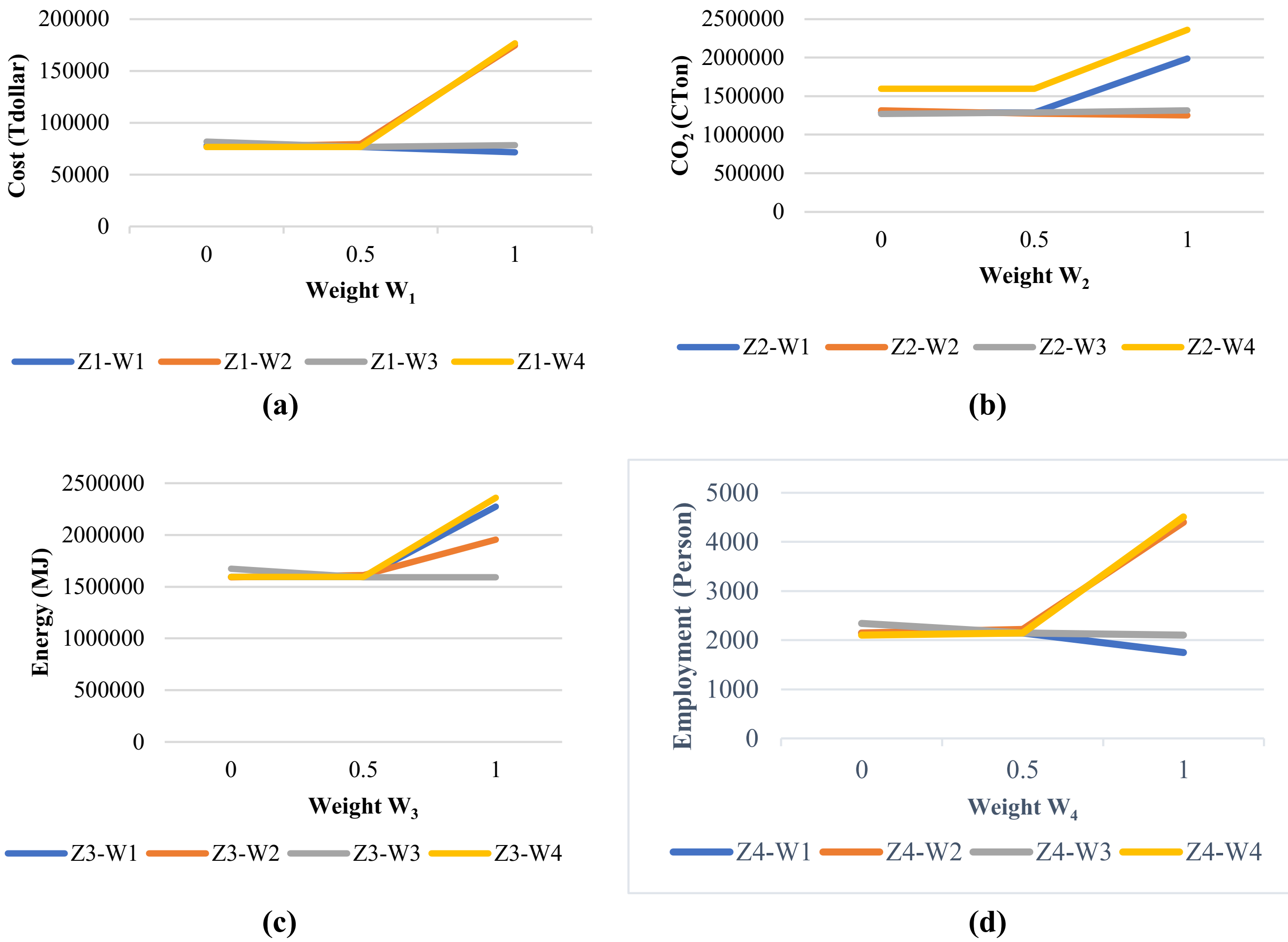
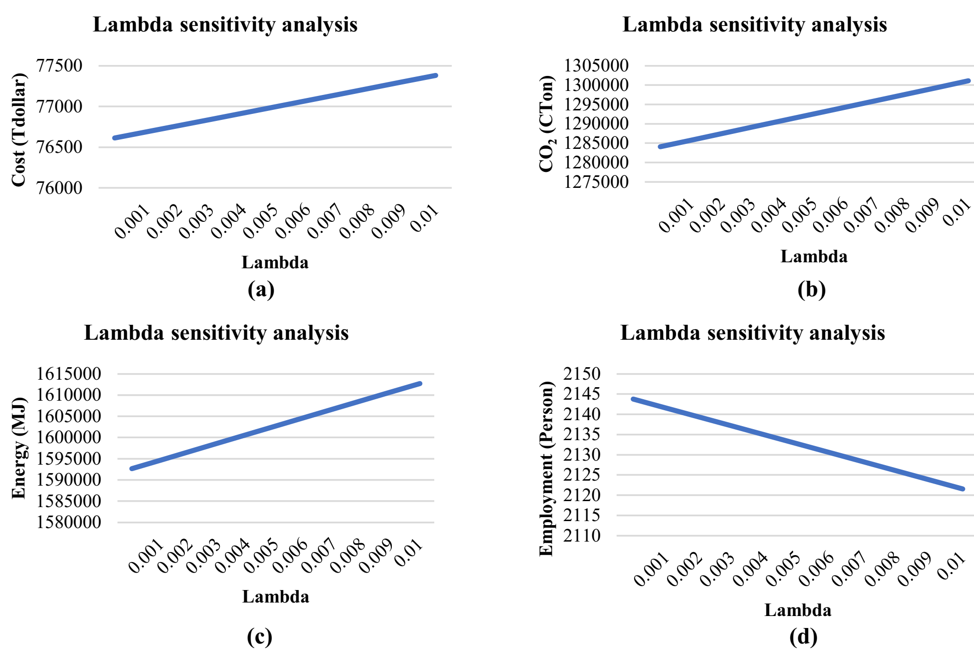


Fig. 5 (**a**) Analyses on the cost objective. (**b**) Analyses on the environmental objective. (**c**) Analyses on the energy objective. (**d**) Analyses on the employment objective

study is based on information about a car and manufacturing company. The company decided to manufacture a car in a car

Fig. 6 (**a**) Variation of λ for the cost objective. (**b**) Variation of λ for the environmental objective. (**c**) Variation of λ for the energy objective. (**d**) Variation of λ for the employment objective



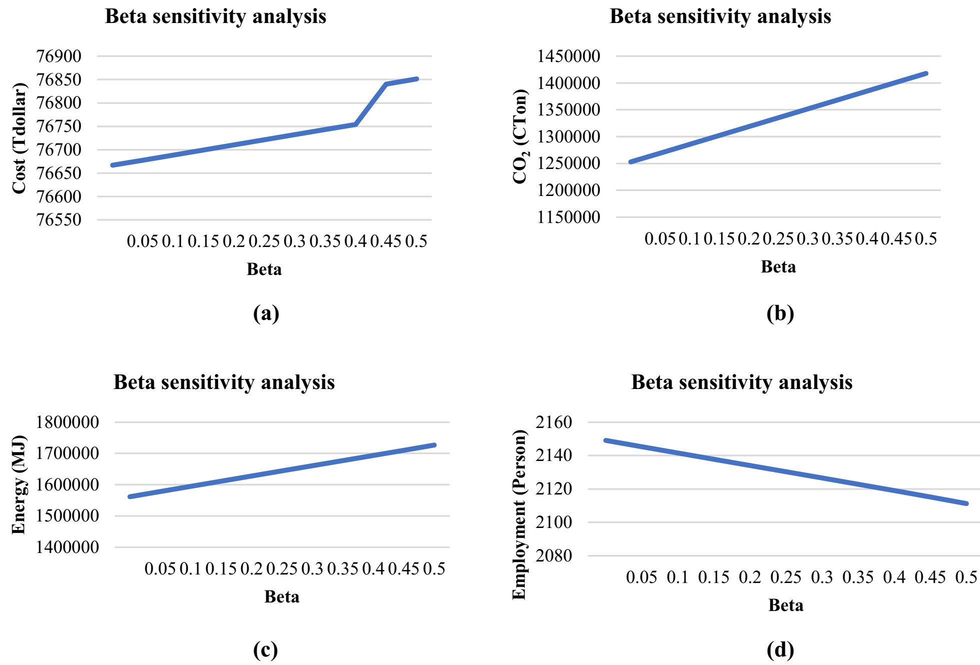


Fig. 7 (**a**) Variations of β for the cost objective. (**b**) Variations of β for the environmental objective. (**c**) Variations of β (the importance factor of variance) versus energy objective. (**d**) Variations of β (the importance factor of variance) versus employment objective

manufacturing company, including suppliers, manufacturing centres, distribution centres, retailing and collection, repairing, and recycling centres. The main manufacturing centre of this company is in Semnan, Iran. Figure 3 addresses the closed-loop supply chain for computing 2.4. EIA based on ReCiPe 2008, energy impact assessment based on CED, and SIA based on GSLCAP.

Results of the global criterion

The results are given in Table 2 and Figs. 3 and 4. Generally, we have three scenario demands with pessimistic, optimistic, and possibilistic. The amounts of the parameters are estimated, where weights are equal to 0.25. The value of the gap between the proposed and base model is 1.2% according to the objective of Lp-metric, as shown in Table 2 and Fig. 3, and gap amount of robust objective function and MAD and

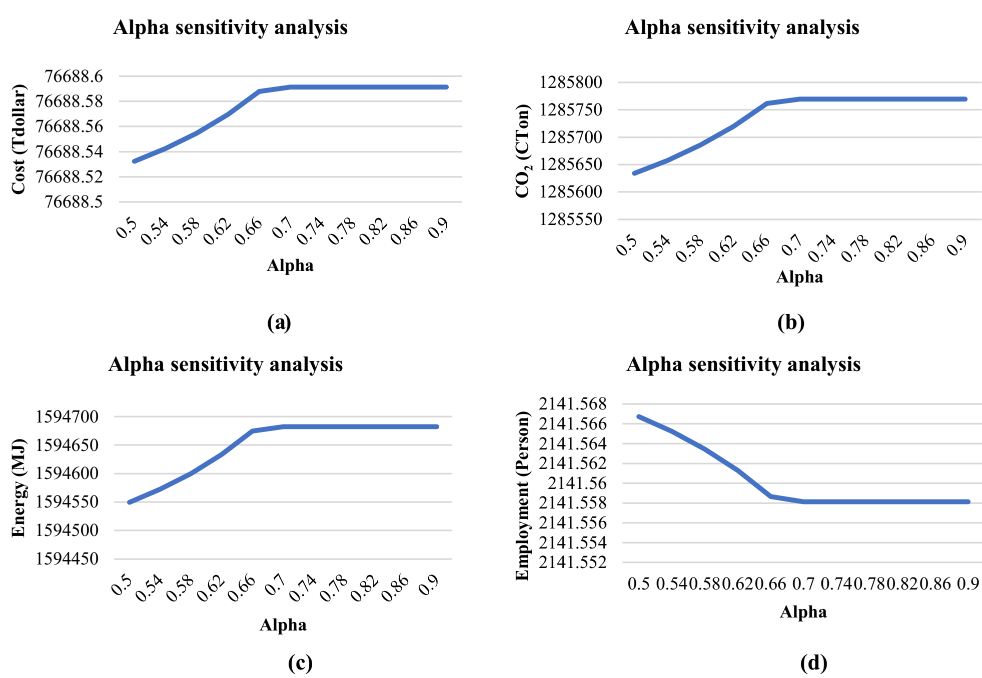


Fig. 8 (**a**) Variations of α (confidence level) versus cost objective. (**b**) Variations of α (confidence level) versus environmental objective. (**c**) Variations of α (confidence level) versus energy objectives. (**d**) Variations of α (confidence level) versus employment objectives

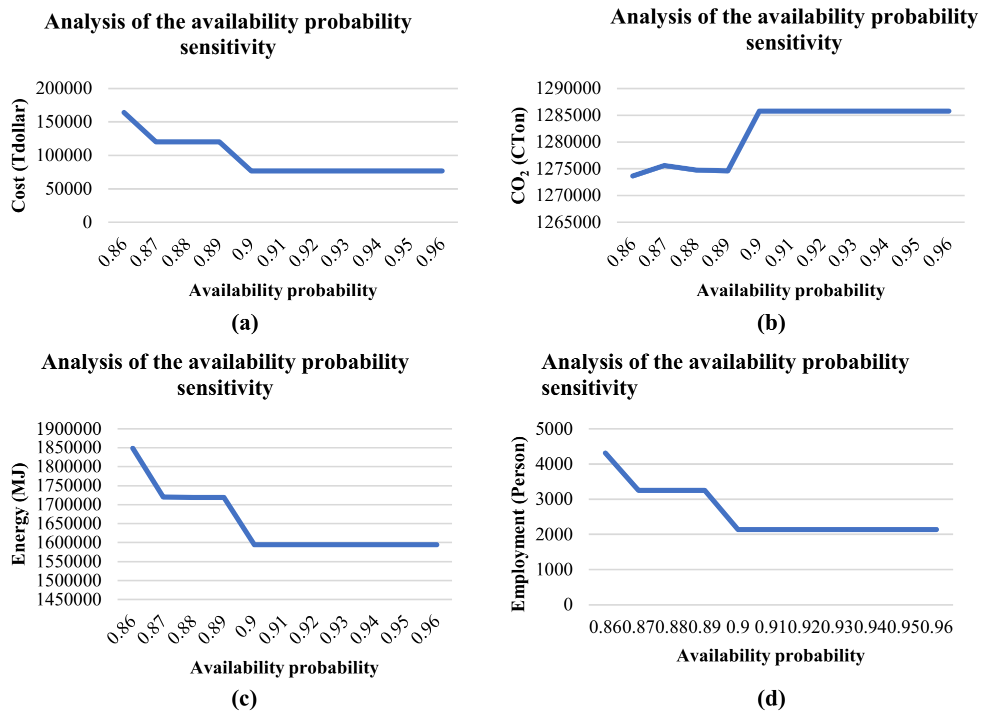


Fig. 9 (**a**) Variations of *p*ravailability probability versus cost objective. (**b**) Variations of *p*ravailability probability versus environmental objective. (**c**) Variations of *p*ravailability probability versus energy objective. (**d**) Variations of *p*ravailability probability versus employment objective

VaR model objective with considering risk is 0.05% and 0.1% in Lp-metric objective (Table 3 and Fig. 3).

The proposed model is linked with the reality of the hosting (domestic) country, i.e. Iran, and the type of business which it runs although the model is complex, due to the presence of resilience, availability, risk measure, and robustness, for SCN design. The location and flow material are illustrated in Fig. 4.

Sensitivity analysis

The results of the variation in the W_i model's objective weights, the parameters α and λ, the CVaR criterion, and the parameter β in the robustness coefficient are presented in Table 3 and Fig. 5a–d. As can be seen, by increasing the importance of the cost objective, the cost decreases, the pollutants and energy increase, and employment decreases (Table 3 and Fig. 5a). Also, increasing the importance of the environmental objective leads to an increase in the value of cost, energy, and employment and a decrease in the pollutants as shown in Table 3 and Fig. 5b. Furthermore, Table 3 and Fig. 5c indicate that when the importance of the energy objective increases, the cost, energy, and employment decrease and the pollutant level raises. Finally, the importance of employment objective has a direct relationship with the values of cost, pollutant level, energy, and employment level, as presented in Table 3 and Fig. 5d.

The parameter λ is CVaR index and fluctuates between 0 and 0.01. By increasing the λ value of the cost, the amounts of pollution and energy consumption increase, and the employment decrease, so more attention is paid to the risks (see Fig. 6a–d). The parameter β is the important factor of the variation variance, ranging from 0 to 0.5. Increasing β leads to an

Table 4 Medium and large-scale problems

Problem	$\lvert S\rvert * \lvert M\rvert * \lvert D\rvert * \lvert R\rvert * \lvert C\rvert * \lvert K\rvert * \lvert E\rvert * \lvert Sc\rvert * \lvert P\rvert * \lvert T\rvert * \lvert S'\rvert$	Variable	Binary variable	Free variable	Linear variable	Constraint
P1	3*3*3*3*3*3*3*3*3*3*3	2289	21	41	2227	2264
P2	4*4*4*4*4*4*4*4*4*4*3	6829	28	41	6760	6797
P3	5*5*5*5*5*5*5*5*5*5*3	16241	35	41	16165	16952
P4	7*7*7*7*7*7*7*7*7*7*5	101359	49	61	101249	121886
P5	10*10*10*10*10*10*10*10*10*10*3	249151	70	41	249040	375077
P6	10*10*10*10*12*12*12*12*12*12*4	577331	76	51	577204	843363
P7	100*4*100*100*100*100*100*100*7*3*3	3245185	604	41	3244540	63107681
P8	15*15*15*15*15*15*15*15*15*15*5	2075855	105	61	2075689	4303246

Table 5 Results of the Lagrangian solutions, i.e. upper bound and lower bound with the exact method

Prob.	Lower bound				Proposed model		Upper bound		GAP$_1$	GAP$_2$	GAP$_3$
	LP-Relax$0\leq X\leq 1$ (A)	Time GAMS	Lagrangian relaxation (B)	Time GAMS	Main model (C)	Time GAMS	Fix-and-optimize (D)	Time GAMS			
P1	10862.2	2.0	68789.66	56.84	76688.9	8.40	81881.7	39.6	−86%	−10%	7%
P2	15720.9	3.8	77178.747	574.57	90009.1	93.7	97274.2	186.9	−83%	−14%	8%
P3	21307.4	11.3	87176.36	7183.44	111813.3	1082.9	113892.4	224.7	−81%	−22%	2%
P4	44956.5	843.1	104501.87	12358.22	*127011.4	*3705.6	156705.7	5678.3	−65%	−18%	23%
P5	74585.4	2967.0	130325.23	162358	*165745.4	*28810	200551.9	23220.3	−55%	−21%	21%

*Solved by NEOS Server, GAP$_1$= (A-C)/C, GAP$_2$= (B-C)/C, GAP$_3$= (D-C)/C

increase in the value of the cost, amounts of pollution, and energy consumption and a decrease in employment, so risks are paid more attention to in these cases (see Fig. 7a–d). The parameter α is considered the confidence level, ranging between 0.5 and 0.95. By increasing the value of α, the amounts of cost, pollution, and energy consumption increase up to a point and then remain constant. Further, the employment trend drops and then remains constant (Fig. 8a–d). The value of the availability probability (*pr*), which is assumed to be identical for all the scenarios and facilities, fluctuates between 0.5 and 0.96. Figure 9 a–d illustrate that increasing the availability probability leads to a decrease in the amounts of financial, energy, and social goals to a point and then fixed. Further, pollution increases and then remains constant.

In addition to the above analyses, the results of the medium and large-scale test problems are given in Table 4.

Objective functions (50), (51), (52), and (53) are Lagrangian relaxation of cost, EIA, CED, and SIA based on objective (1) to (4). Lagrangian relaxation and steps of the proposed model are as follow (Fig. 10). Results of solving P1 problem are shown in Fig. 11a–d. These figures show that when iterations of algorithm continue, the convergence of Lagrangian relaxation happens in all objectives. When the scale of the model is increased, the time of solution is increased too (Table 5).

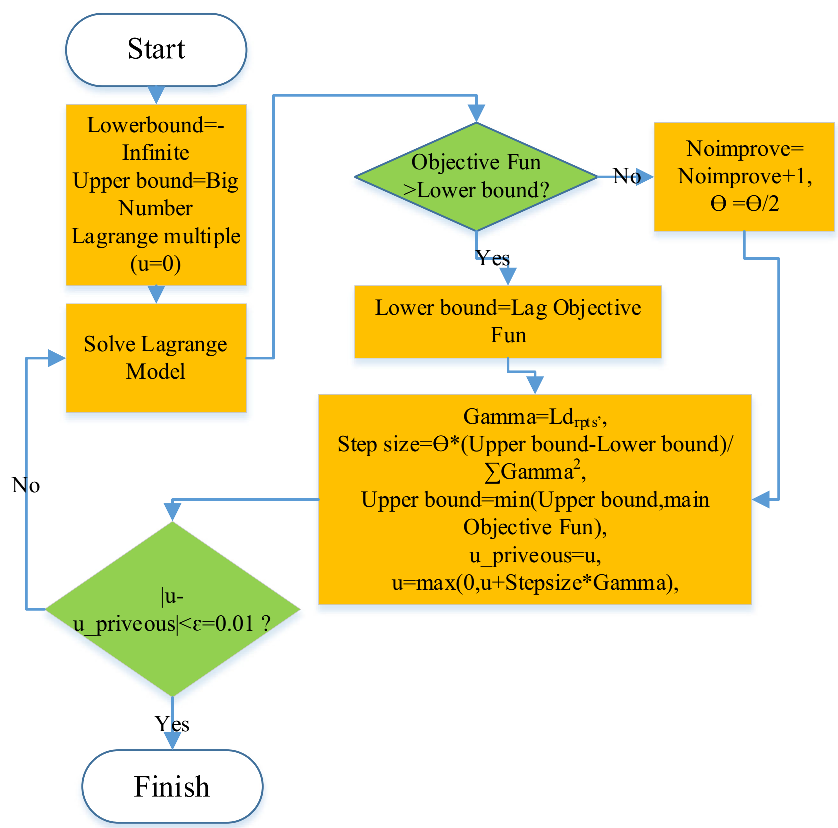


Fig. 10 Lagrangian relaxation algorithm

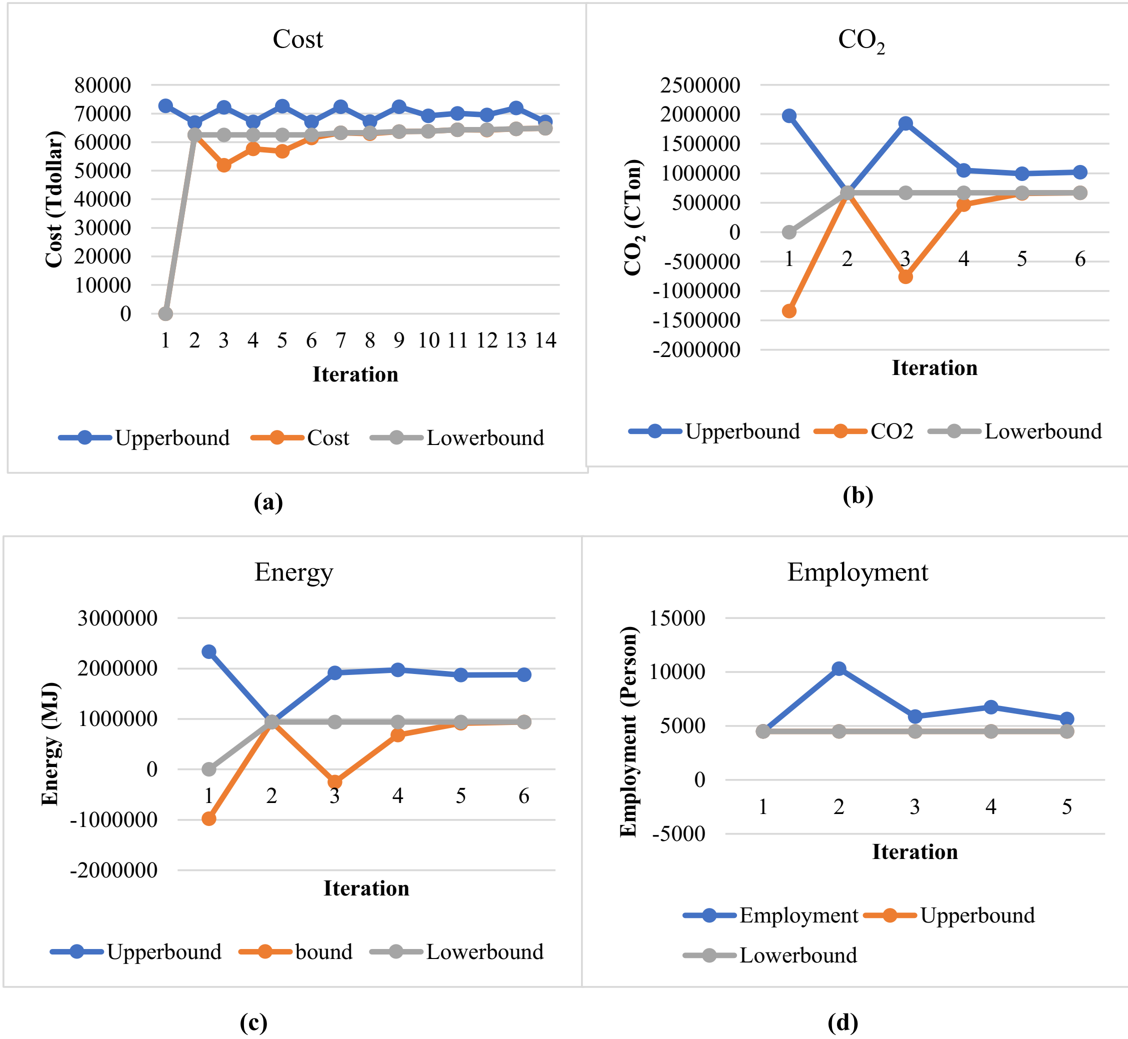


Fig. 11 (**a**) Lagrangian relaxation algorithm for cost. (**b**) Lagrangian relaxation algorithm for CO2. (**c**) Lagrangian relaxation algorithm for energy. (**d**) Lagrangian relaxation algorithm for employment

$$minLRobj_1 = obj_1 + \sum_r \sum_p \sum_t \sum_{s'} ud_{rpts'} Ld_{rpts'}, \quad (50)$$

$$minLRobj_2 = obj_2 + \sum_r \sum_p \sum_t \sum_{s'} vd_{rpts'} Ld_{rpts'}, \quad (51)$$

$$\text{min}LRobj_3 = obj_3 + \sum_r \sum_p \sum_t \sum_{s'} wd_{rpts'} Ld_{rpts'}, \quad (52)$$

$$maxLRobj_4 = obj_4 + \sum_r \sum_p \sum_t \sum_{s'} yd_{rpts'} Ld_{rpts'}. \quad (53)$$

Such that:

$$Ld_{rpts'} = -\sum_d Qdr_{drpts'} + dem_{rpts'} + z_{rpts'}, \quad \forall r, p, t, s' \quad (54)$$

$$ud_{rpts'}, vd_{rpts'}, wd_{rpts'}, yd_{rpts'} \geq 0 \quad \forall r, p, t, s' \quad (55)$$

Constraints (5)to (15)and (17)to (32)

Finally, the solutions found by the Lagrangian relaxation algorithm in comparison with the optimal results from the GAMS software are given in Table 5.

Conclusion

Vital and global issues such as designing the supply chains, considering environmental and social welfare, and lowering energy consumption in the chain have attracted a lot of attention in recent years. The management of the sustainable closed-loop supply chain has recently gained much importance. According to the governmental laws and legislation, the issues of environmental impact, employment opportunities, and energy consumption, and customer and beneficiary expectations should be considered in the supply chain management and are regarded as major factors between competitors.

This paper provided a new closed-loop supply chain under uncertainty with the use of resiliency, sustainability, and reliability dimensions among the first studies. To model this problem, a two-stage stochastic programming approach was used. To create robust solutions against uncertainty, a conditional value at risk criterion was contributed. The proposed model minimizes the total cost and environmental pollution and maximizes the job opportunities as the social factor. To solve the model, the Lp-metric method was employed to transform this multi-objective model into a single objective one. Since this closed-loop supply chain model was complex and NP-hard, a Lagrangian relaxation method with fix-and-optimize heuristic was employed to find the upper and lower bounds for the model via different random test problems. With an extensive analysis, the proposed model shows an improvement to the total cost, CO_2 emissions, job opportunities, and energy consumption.

The present study proposed to solve an optimization model for closed-loop supply chain using fix-and-optimize and Lagrangian relaxation of using objectives causing a lower bound and an upper bound to be obtained for the model. This type of modelling applies to both automotive supply chain and the design of other supply chain networks. Without a doubt, the proposed solution algorithm is successful to address the proposed problem. However, it is highly recommended to use recent advances in metaheuristics for solving the proposed model for future works.

Author contribution Dr. Muhammad Salman Shabbir: conceptualization, formal analysis, investigation, methodology, software, validation, original draft, visualization, and review and editing

Dr. Arshad Mahmood: supervision; project admiration, and review and editing

Roy Setiawan: supervision and review and editing

Dr. Chairun Nasirin: supervision and review and editing

Rusdiyanto Rusdiyanto: review and editing

Gazali Gazali: review and editing

Dr. Mohd Anuar Arshad: review and editing

Dr. Shahid Khan: review and editing

Fatima Batool: review and editing

Data availability The authors declare that the data are not available and can be presented upon the request of the readers.

Declarations

Ethics approval The authors declare that there is no conflict of interest.

Consent to participate The authors declare that they agree with the participation of the journal.

Consent for publication The authors declare that they agree with the publication of this paper in this journal.

Conflict of interest The authors declare no competing interests.

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